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Influence of Organic Matter on the Estimation of Saturated Hydraulic Conductivity

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ABSTRACT

Estimation of soil hydraulic properties by pedotransfer functions (PTFs) can be used in many applications. Some of existing PTFs estimate saturated hydraulic conductivity (K_s) of the soil, using organic matter (OM) content as one of the input variables. Several authors have shown an increase in K_s with increasing OM content, a soil property that presumably improves soil structure. We used three popular PTFs to examine the relationship between OM content and K_s. We also used data originating from the U.S., Hungary, and the European HYPRES database, to develop additional PTFs with the Group Method of Data Handling (GMDH). It appears that existing PTFs negatively correlate K_s with OM content for some soils. We found indications of negative relationship between OM content and K_s with the newly developed PTFs both for directly estimated K_s, and for K_s estimated via the effective porosity of the soil, using a generalized Kozeny–Carman approach. It is not straightforward to define the exact range of soils with the inverse relationship between OM and K_s. The range appeared to be data set dependent, but it was extensive within the valid input range of each PTF.

HYDRAULIC CONDUCTIVITY is one of the essential inputs to most simulation models used in soil and land research. When such data is needed for large areas of land, estimations using PTFs offer a competitive alternative to the cumbersome and costly direct measurements. Data on soil texture (sand, silt, and clay content) and bulk density (D_b) are the two most commonly used inputs to such PTFs. Some authors however include the OM content in the list of inputs, since OM is known to affect the hydraulic properties of the soil. It is often assumed that greater OM content in the soil will result in higher saturated hydraulic conductivity (K_s). The rationale behind such assumption is that better soil aggregation is linked to greater OM contents (e.g., Beare et al., 1994), OM content and D_b tend to be negatively correlated (e.g., Adams, 1973; Rawls et al., 2005) and therefore OM content and porosity are thought to be positively correlated. Greater porosity is supposed to lead to greater hydraulic conductivity.

Several authors have shown in their experiments that such is the case for their soils (e.g., Auerswald, 1995; Mbagwu and Auerswald, 1999; Lado et al., 2004). These studies were specifically designed to examine the relationships between a number of soil hydraulic properties and soil aggregation on limited number of soils, and typically involved measurements of soil hydraulic properties in repacked soil columns. The opposite effect has, however been estimated by Nemes et al. (2005) and Rawls et al. (2005) who used soil hydraulic PTFs as a tool. Nemes et al. (2005) performed scenario studies, and simulated the effect of soil properties, such as OM content on certain soil water balance components. They simulated the increase of the OM content of a Chromic Cambisol (Dystric Haplustept). Estimated K_s was lower for higher OM contents with a PTF based on a Hungarian data set. Rawls et al. (2005) estimated effective porosity (ϕ_e) using data from the USDA-NRCS National Soil Characterization database (Soil Survey Staff, 1997) and used the relationship between K_s and ϕ_e suggested by Ahuja et al. (1984) and Rawls et al. (1998). They developed a figure, which showed cases when their PTF predicted lower K_s for higher OM content for certain soil textures.

Soil hydraulic PTFs are, in most cases, not specifically developed to address one particular problem, but are developed from a larger data collection to potentially provide information to many studies. The underlying databases usually report on soil hydraulic properties determined on undisturbed soil samples. A PTF user will obtain predictions that reflect the inter-correlations of data in the underlying database. Subsequent application of PTF estimates in simulation models without knowing the nature of such correlations may lead to inexplicable results and possibly to incorrect or inefficient decisions.

This study aims to examine the effect of changes in OM content on the estimation of K_s. Existing PTFs are first examined and additional PTFs are developed from three different data sets. Two approaches are applied to obtain estimates of K_s. We estimate K_s directly, and also use the modified Kozeny–Carman approach, as described by Ahuja et al. (1984), to characterize soils for which we found the inverse relationship between OM and K_s.

MATERIALS AND METHODS

Published Pedotransfer Functions

We have searched through the international literature to identify PTFs that predict K_s from a set of soil physical data including OM content as one of the predictors. Three sources, namely Vereecken et al. (1990), Wösten et al. (1999), and Wösten et al. (2001) that meet the above criteria were identified.

Vereecken et al. (1990) has developed PTFs from a data set from Belgium. The following formula has been derived to estimate K_s:

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Abbreviations: CPM, complexity penalty multiplier; D_b, bulk density; GMDH, Group Method of Data Handling; K_s, saturated hydraulic conductivity; OM, organic matter; PTF, pedotransfer function; ϕ, total porosity; ϕ_e, effective porosity; θ_{33}, water content at −33 kPa matric potential.

$$\ln(K_s) = 20.62 - 0.96 \times \ln(\mathrm{CL}) - 0.66 \times \ln(\mathrm{SA}) - 0.46 \times \ln(\mathrm{OM}) - 8.43 \times \mathrm{D_b} \quad [1]$$

where CL and SA refer to the amount of clay and sand content (%) of the soil according to the USDA classification (USDA, 1951), OM is the organic matter content (%), and D_b is the soil bulk density (g cm^{-3}). They have also developed other PTFs using more detailed particle-size distribution data. The resulting equation for the estimation of K_s is:

$$\ln(K_s) = 18.096 - 0.324 \times \mathrm{f1} + 0.312 \times \mathrm{f2} - 0.305 \times \mathrm{f3} + 0.363 \times \mathrm{f5} + 0.370 \times \mathrm{f6} - 0.774 \times \mathrm{OM} - 9.056 \times \mathrm{D_b} \quad [2]$$

where f1 to f6 are principal components of the textural fractions, and OM and D_b are defined as above.

Wösten et al. (1999) developed the following equation from data of the European HYPRES database to estimate K_s:

$$\ln(K_s) = 7.75 + 0.0352 \times \mathrm{SI} + 0.93 \times (\mathrm{TOPSOIL}) - 0.967 \times \mathrm{D_b^2} - 0.000484 \times \mathrm{CL^2} - 0.000322 \times \mathrm{SI^2} + 0.001 \times \mathrm{SI^{-1}} - 0.0748 \times \mathrm{Om^{-1}} - 0.643 \times \ln(\mathrm{SI}) - 0.01398 \times \mathrm{D_b} \times \mathrm{CL} - 0.1673 \times \mathrm{D_b} \times \mathrm{OM} + 0.02986 \times (\mathrm{TOPSOIL}) \times \mathrm{CL} - 0.03305 \times (\mathrm{TOPSOIL}) \times \mathrm{SI} \quad [3]$$

Variables in the equation that were not previously defined are: SI, which refers to silt content (%) of the soil according to the USDA classification (USDA, 1951), and TOPSOIL which is a categorical variable, having a value of 1 if the soil sample comes from the topsoil (i.e., A or E horizon, according to the FAO soil classification [FAO, 1990] or 0 if it is from the subsoil).

Wösten et al. (2001) developed PTFs specifically for sandy soils and for loam and clay soils (according to the Dutch soil textural classification) from the available soils data in the Netherlands. Their regression analyses yielded the following equation for sandy soils:

$$\ln(K_s) = 45.8 - 14.34 \times \mathrm{D_b} + 0.001481 \times \mathrm{SI^2} - 27.5 \times \mathrm{D_b^{-1}} - 0.891 \times \ln(\mathrm{SI}) - 0.34 \times \ln(\mathrm{OM}) \quad [4]$$

For loam and clay soils, these authors obtained:

$$\ln(K_s) = -42.6 + 8.71 \times \mathrm{OM} + 61.9 \times \mathrm{D_b} - 20.79 \times \mathrm{D_b^2} - 0.2107 \times \mathrm{OM^2} - 0.01622 \times \mathrm{CL} \times \mathrm{OM} - 5.382 \times \mathrm{D_b} \times \mathrm{OM} \quad [5]$$

Data Sets Used to Develop New Pedotransfer Functions

Three databases were used to derive new PTFs to estimate K_s. The HYPRES database (Wösten et al., 1999) contains basic soil data and soil hydraulic data from 12 European countries. The HUNSODA database (Nemes, 2002) comprises soil data collected in Hungary. These data are not included in the HYPRES database. The third set of data originated from the USA and has previously been used by Rawls et al. (1998). All three databases were filtered to select soils that have data on soil texture, D_b and OM content, and have laboratory-measured K_s. This selection left us with European (EUR, N = 1108), Hungarian (HUN, N = 131), and U.S. (USA, N = 886) data sets. The three data sets were used to develop PTFs using the same methodology, so the differences between data sets were the only factor that was changed. We note, that the EUR data set is not identical to the set used by Wösten et al. (1999) to develop PTFs, and methods we use are also different.

Table 1. Summary statistics of selected soil properties in three data sets used to develop pedotransfer functions; EUR–the European data set; HUN–the Hungarian data set; USA–the U.S. data set; sand, silt, and clay content defined according to USDA (1951) classification; D_b–the bulk density; OM–the organic matter content; K_s–the saturated hydraulic conductivity; θ_{33}–the soil water content at matric potential −33 kPa.

	Sand	Silt	Clay	D_b	OM	K_s	θ_{33}
	%			g cm^{-3}	%	cm d^{-1}	m^3 m^{-3}
				EUR			
min	0.49	0.00	0.00	0.90	0.09	0.01	0.027
max	100.00	81.16	80.00	1.90	7.89	2423.00	0.598
ave	30.24	41.93	27.83	1.46	1.27	129.39	0.325
std	28.51	20.59	17.44	0.19	1.20	293.86	0.116
med	16.60	42.77	24.50	1.49	0.89	25.65	0.327
				HUN			
min	0.99	1.80	1.46	1.00	0.10	0.01	0.039
max	96.13	82.40	49.04	1.76	6.48	742.80	0.563
ave	38.21	41.59	20.20	1.46	2.05	78.60	0.324
std	30.87	23.42	13.89	0.15	1.53	135.08	0.109
med	30.07	47.70	15.70	1.48	1.83	11.20	0.347
				USA			
min	0.20	0.00	0.00	0.91	0.10	0.01	0.013
max	99.70	73.80	83.50	1.86	4.40	197.00	0.611
ave	78.94	10.38	10.68	1.50	0.64	17.60	0.165
std	21.55	13.63	12.04	0.16	0.79	27.00	0.112
med	86.70	5.00	6.05	1.52	0.30	4.83	0.144

Table 1 and Fig. 1 show the summary statistics and the scatter plot of selected soil properties of the three data sets. In all three data sets, soil textural fractions have been determined according to the FAO/USDA particle-size classification system (FAO, 1990; USDA, 1951). There are apparent differences between data sets, with the USA set having, on average, (i) substantially higher average sand content and lower silt and clay content than the other two sets, and (ii) lower OM content than the other two data sets. Soils in the HUN data set have the highest average OM content. The USA set has the lowest K_s at database level and the EUR set the highest. The ranges of OM contents covered by the different data sets were also different, the USA set providing the narrowest range and the EUR set the widest.

Development of new Pedotransfer Functions

We used GMDH (Farrow, 1984) to describe the relationships between input and output variables. The method performs an automated selection of essential input variables and builds hierarchical polynomial regressions of desired complexity to estimate the output variable. First, polynomials are built from some of the input variables. Such polynomials may be better predictors of the output variable than some of the input variables alone, and so the best ones are then considered to serve as new inputs to new polynomials. The final polynomial to estimate the output is then built from a mix of original input variables and polynomials derived from those input variables. Examples for the application of this technique to estimate soil hydraulic properties can be found in Pachepsky et al. (1998), Pachepsky and Rawls (1999), Ungaro and Calzolari (2002), and Tomasella et al. (2003). For this application we used the commercial GMDH software ModelQuest (AbTech Corp., 1996). Values of non-problem specific variables were set to the default value in the software. The maximum number of layers in the model was set at four and the maximum number of terms allowed in the first (input) layer was set at 15. The

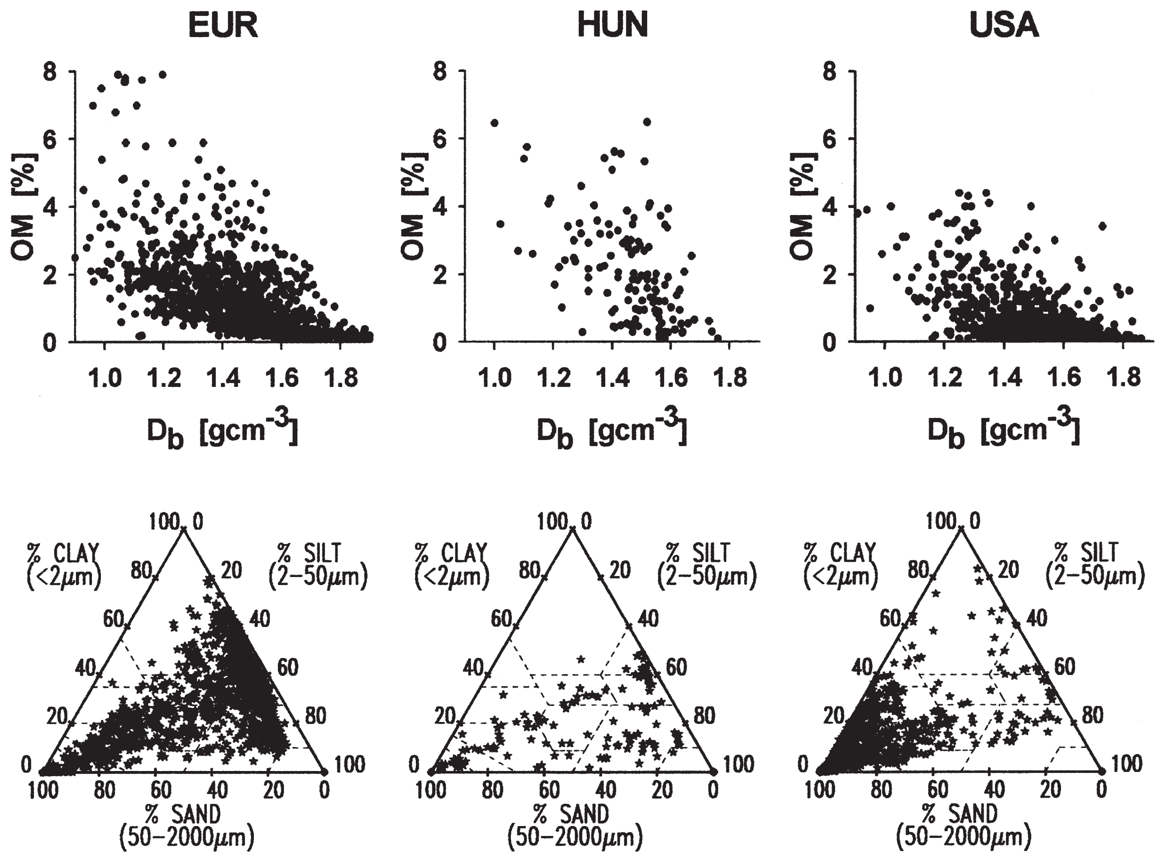

Fig. 1. Summary of physical properties of the three data sets. (OM–the organic matter content; D_b–the bulk density; EUR–the European data set; HUN–the Hungarian data set; USA–the U.S. data set).

software uses a complexity penalty multiplier (CPM) to select the final model. The CPM adjusts the trade-off between network complexity and modeling accuracy. We used the default value of one for CPM, which allows ModelQuest to choose the best estimate for the complexity penalty based on the variance of the output variable observations.

Two approaches were implemented to obtain information on the sensitivity of K_s estimates to the OM content. In the first approach, K_s was directly estimated from particle-size data, OM content and D_b of the soils. In the second approach, K_s was estimated using an indirect approach that uses both porosity and the slope of the water retention curve as proposed by Ahuja et al. (1984). It is a generalized Kozeny-Carman (Carman, 1956) equation relating K_s to ϕ_e in the following form:

$$K_s = C\phi_e^m \qquad [6]$$

where K_s = saturated hydraulic conductivity (mm h^{-1}); ϕ_e = effective porosity (m^{3}m^{-3}) (total porosity, ϕ, minus water content at -33 kPa matric potential, θ_{33}); and C and m are empirically derived constants. As our goal in this study was to give an indication whether and for which soils the inverse relationship between K_s and OM content is estimated, we did not use the optimized C and m coefficients of any authors in Eq. [6] to obtain estimates of K_s. Rather, we used the change in ϕ_e as an indicator of the direction of change in K_s. While calibrating Eq. [6], many authors associate greater K_s with greater ϕ_e (e.g., Rawls et al., 1998; Timlin et al., 1999; Schaap and Lebron, 2001). To implement this approach, ϕ and θ_{33} were estimated separately from soil texture data and OM content, and their difference was calculated to obtain ϕ_e. Bulk density was not used in the estimations as it is in direct correlation with ϕ, one of the estimated properties.

In total, we developed nine sets of predictive equations: from each data set (EUR, HUN, USA) we estimate K_s, ϕ, and θ_{33}. Since we worked with a number of PTFs in this study, and we did not apply the PTFs to any particular test data sets, we found it undesirable to report absolute values of estimated K_s, and associated statistics (those can be obtained from the corresponding author on request). Rather we examined the estimations in relative terms, aiming to identify group properties of soils, for which inverse relation between OM content and K_s were estimated. To obtain an indication of such relationships, we examined the first-order partial derivative of each predictive equation with respect to OM. We followed this approach for both the published and the newly developed PTFs.

RESULTS AND DISCUSSION

Published Pedotransfer Functions

We use the partial derivative with respect to OM of each PTF to indicate the estimated relationships between OM and K_s. If the derivative has a positive value, an increase of the OM content results in an increase in the estimated K_s value. When the derivative is negative, an inverse relationship is estimated, and increase in OM will yield decrease in K_s. The first-order partial derivative with respect to OM of the PTF of Vereecken et al. (1990) from Eq. [1] is:

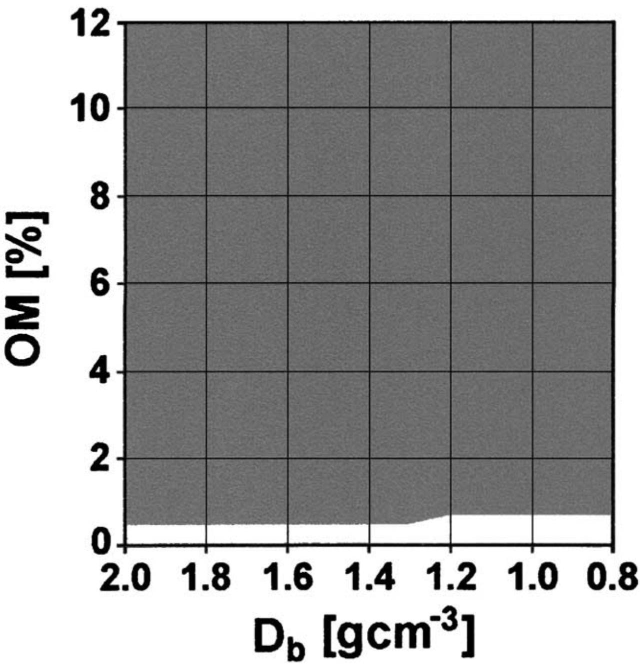

Fig. 2. Relationship between organic matter (OM) and saturated hydraulic conductivity (K_s) from the pedotransfer function of Wösten et al. (1999); relationship is inverse in the gray area and positive in the blank area.

$$\frac{d}{d(OM)} \ln(K_s) = -\frac{0.46}{OM} \quad [7]$$

Since the above equation will yield a negative value for any valid OM contents, the user of this PTF will obtain lower $\ln(K_s)$—and therefore K_s—for the soil with greater OM content, in all OM content ranges, if the other input properties of the soils are the same. The derivative is not defined for OM = 0. The partial derivative with respect to OM of the alternative equation developed by Vereecken et al. (1990) from the same data using more detailed information on soil texture (Eq. [2]) is:

$$\frac{d}{d(OM)} \ln(K_s) = -0.774 \quad [8]$$

Clearly, this equation will also result in estimating lower K_s for higher OM contents. The PTF developed by Wösten et al. (1999) has two terms where the OM content appears (Eq. [3]). One of the terms includes the interaction between D_b and OM. The partial derivative with respect to OM is as follows:

$$\frac{d}{d(OM)} \ln(K_s) = \frac{0.0748}{OM^2} - 0.1673\ D_b \quad [9]$$

The range of OM content for which Eq. [9] is negative depends on D_b. Figure 2 shows combinations of OM and D_b for which the derivative is positive or negative. With the exception of a narrow range of soils with low OM content (OM < 0.8 where $D_b < 1.3$ and OM < 0.6 where $D_b > 1.3$) the derivative is negative. A decrease in K_s is estimated with increasing OM content for a wide range of soil properties represented in the gray area in Fig. 2. Wösten et al. (2001) developed PTFs separately for sandy

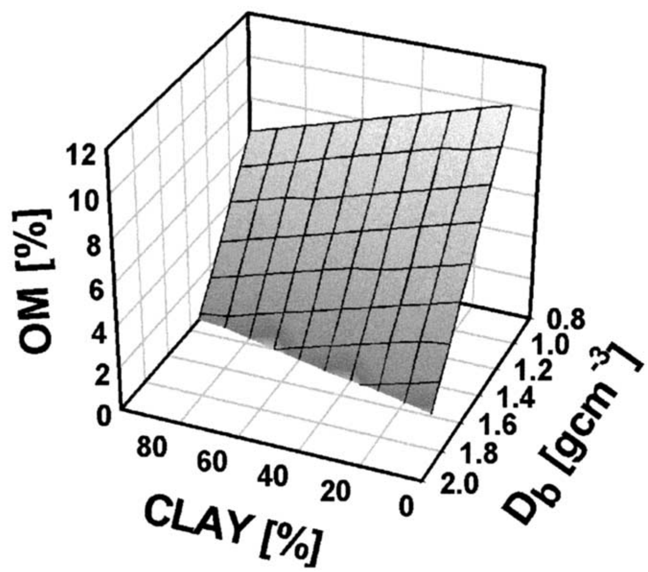

Fig. 3. Relationship between organic matter (OM) and saturated hydraulic conductivity (K_s) from the pedotransfer function (PTF) of Wösten et al. (2001), for loam and clay soils. Relationship is inverse if the soil is represented by a point above gray surface and positive if it is below the gray surface. This PTF is not applicable for soils with clay content below 8%.

soils and for loam and clay soils (Eq. [4] and [5]). In the model of Eq. [4] they developed for sandy soils, the sole term involving OM content is $[-0.34\ln(OM)]$. This will yield a partial derivative as follows:

$$\frac{d}{d(OM)} \ln(K_s) = -\frac{0.34}{OM} \quad [10]$$

Equation [10] will yield a negative value for any valid (positive) OM contents. A user of this PTF will obtain lower K_s for the soil with greater OM content, if the other input properties of the soils are otherwise equal. The derivative is more complex for the loam and clay soils, as OM content appears in four terms in Eq. [5], including interactions with clay content and D_b:

$$\frac{d}{d(OM)} \ln(K_s) = 8.71 - 0.4214\ OM - 0.01622\ CL - 5.382\ D_b. \quad [11]$$

The threshold of OM, at which the outcome of Eq. [11] switches sign, changes with clay content and with D_b. We developed Fig. 3 to visualize the surface representing the equation: $8.71 - 0.4214OM - 0.01622CL - 5.382\ D_b = 0$. If a soil falls above the gray surface, the right-hand side of Eq. [11] is negative. This indicates that OM and K_s are negatively correlated. If a soil is represented by points below that surface, estimated K_s increases with increasing OM. The higher clay contents and D_b the wider is the OM range for which the negative relationship is estimated between OM and K_s. In summary, all examined PTFs predict negative relationships between OM and K_s for a certain range of soil properties. However, this range differs for the different PTFs.

Table 2. Pearson correlation coefficients for selected soil properties in three data sets; EUR–the European data set; HUN–the Hungarian data set; USA–the U.S. data set; sand, silt and clay content defined according to the USDA (1951) classification; D_b–the bulk density; OM–the organic matter content; K_s–the saturated hydraulic conductivity; θ_{33}–the soil water content at matric potential −33 kPa.

	Silt	Clay	D_b	OM	$\log_{10}(K_s)$	θ_{33}
			EUR			
Sand	−0.794***	−0.697***	0.437***	−0.155***	0.356***	−0.789***
Silt		0.118***	−0.153***	−0.021	−0.104***	0.404***
Clay			−0.533***	0.277***	−0.460***	0.812***
D_b				−0.605***	0.023	−0.679***
OM					−0.013	0.384***
$\log_{10}(K_s)$						−0.439***
			HUN			
Sand	−0.905***	−0.696***	0.209*	−0.496***	0.557***	−0.815***
Silt		0.325***	−0.281**	0.498***	−0.438***	0.695***
Clay			0.009	0.262**	−0.499***	0.640***
D_b				−0.506***	−0.210*	−0.339***
OM					−0.202*	0.466***
$\log_{10}(K_s)$						−0.599***
			USA			
Sand	−0.860***	−0.817***	0.053	−0.054	0.646***	−0.813***
Silt		0.408***	−0.161***	0.157***	−0.473***	0.563***
Clay			0.087**	−0.080*	−0.621***	0.819***
D_b				−0.552***	−0.264***	−0.055
OM					−0.074*	0.176***
$\log_{10}(K_s)$						−0.623***

* Significant at the 0.05 probability level.
** Significant at the 0.01 probability level.
*** Significant at the 0.001 probability level.

Newly Developed Pedotransfer Functions

Correlations in the Raw Data

It may be argued that inverse relationship between K_s and OM content in the soil arise, at least partly, due to certain correlations between OM content and some other inputs. For example, if OM content has a significant positive correlation with clay content, an observed negative correlation between OM content and K_s may be due to the negative impact of clay content on K_s. We examined such correlations between soil properties shown in Table 1 in the three input data sets, using Pearson's correlation test (Table 2). The variable of interest, the OM content, is in significant negative correlation with sand content in the EUR and HUN data sets. The correlation is strong in the HUN data set, and less expressed in the EUR set. Correlation between these two variables was not significant at the examined levels for the USA data set. Mostly positive correlations were found while correlating OM content with silt and clay content. There was no significant correlation between OM content and silt content for the EUR data set, and the correlation was negative between OM content and clay content for the USA data set. The dependence of OM on textural variables is strong in the HUN data set (i.e., OM is greater in soils with finer texture), weaker in the EUR data set and is very weak in the USA data set. Interestingly, OM content is in negative correlation with $\log_{10}(K_s)$ for two data sets (HUN, USA) and shows no significant correlation for the EUR set. Organic matter contents and D_b are negatively correlated, and OM content and θ_{33} are positively correlated for all three data sets.

Table 3. Accuracy and reliability of the developed pedotransfer functions for the direct estimation of K_s, in terms of root mean squared residuals of $\log_{10}(K_s)$. Model accuracy is shown in italic in the diagonal of the table. Model reliability has been evaluated using both of the other data sets separately. (EUR–the European data set; HUN–the Hungarian data set; USA–the U.S. data set).

	Test data set		
Development data set	EUR	HUN	USA
EUR	*0.795*	1.411	1.590
HUN	1.447	*0.793*	1.551
USA	2.076	1.632	*0.560*

Direct Estimation of Saturated Hydraulic Conductivity

The saturated hydraulic conductivity was directly estimated using data on sand and clay content, D_b and OM content. Accuracy and reliability of the developed PTFs, in terms of root mean squared residuals of $\log_{10}(K_s)$, are shown in Table 3. Model accuracy has been evaluated using data of the same data set as the development data set. Model reliability has been evaluated using data of both of the other data sets separately. Appendix 1 shows the set of equations obtained using the USA data set. Auxiliary variables x_1 to x_4 represent transformed input variables, which the ModelQuest software calculates automatically from the input data. Auxiliary variables z_1 to z_4 represent intermediate polynomials that are developed during the optimization process as described previously. The transformed output variable is calculated using the above auxiliary variables and is than back-transformed to yield K_s. The GMDH typically generates a set of equations, which is rather long and complicated when all auxiliary variables are substituted into one equation. Therefore, equations for partial derivatives are also complicated. We give an example for one of such equations in the next section. We developed Fig. 4 to visualize the signs of the derivatives, developed from the PTFs using each of the data sets. Results are shown for three levels of sand content (20, 50, and 80%) and five levels of D_b (1.0–1.8 g cm^{-3} by 0.2 g cm^{-3} increments). For each data set, the displayed combination of soil properties was further limited according to the observed range of physical properties in the data sets (compare Table 1 and Fig. 1). Additional boundaries were established based on pair-wise examination of soil physical properties, similarly to Fig. 1 (e.g., sand vs. OM, sand vs. D_b, etc.). Such limitations were necessary to minimize the risk of showing combinations of data that are not represented in the PTF development data set.

Combinations of soil properties have been identified, and are shown in different colors for the different levels of D_b, for which the particular PTF estimates smaller K_s when OM content is increased (i.e., for which the partial derivative is negative). The range of soil properties is shown, for which the estimated K_s decreases when OM content is increased. Graphs *a* to *c*, *e* to *g*, and *i* to *k* show that for each data set and for each selected level of sand content, there is a considerable range of soil properties for which negative relationship between K_s and change to OM content is estimated. The range of such soil properties is widest for the EUR data set. Graphs *d*, *h*, and *l* were derived from the other nine graphs; showing, for each level of sand content, soils for which at least one of the three PTFs estimated negative relationship between K_s and OM content. For most soils, within the input range of the PTFs, at least one of the PTFs estimated such negative relationship. Such is especially pronounced in the middle of the examined range of D_b (1.2–1.6 g cm^{-3}).

Estimation of Saturated Hydraulic Conductivity via Effective Porosity

In the second approach, ϕ and θ_{33} were estimated separately from sand, clay, and OM content, using the same three data sets (EUR, HUN, and USA). Appendix 1 contains an example for such sets of equations developed from the USA data set. Auxiliary variables x_1, x_2, x_4, z_5, and z_6 are used to estimate transformed variables, which are then back-transformed to give estimates of ϕ and θ_{33}. As the estimated ϕ_e for a given soil equals ϕ minus θ_{33}, indication can be obtained about the positive or negative relationship between OM and ϕ_e using the first-order partial derivative of ϕ minus θ_{33} with respect to OM content. For the USA dataset, this partial derivative is:

$$\frac{d}{d(OM)}(\phi - \theta_{33}) = -0.187 + 6.629 \times 10^{-3} \times SA - 5.077 \times 10^{-5} \times SA^2 + 9.932 \times 10^{-3} \times CL - 1.49 \times 10^{-4} \times SA \times CL - 1.241 \times 10^{-4} \times CL^2 - 8.486 \times 10^{-4} \times OM - 3.405 \times 10^{-5} \times SA \times OM + 4.104 \times 10^{-4} \times CL \times OM - 4.433 \times 10^{-3} \times OM^2 \quad [12]$$

We obtained the derivatives for the other two data sets using the same calculations. Figure 5 has been developed to visualize the signs of derivatives developed from the PTFs using each of the data sets. Results are shown in different colors for 10 levels of sand content (5–95% with increments of 10%) in Graphs *a* to *c* for the three data sets. Similarly to Fig. 4, for each data set, the displayed combination of soil properties were limited according to the observed range of physical properties in the data sets (compare Table 1 and Fig. 1) to avoid showing combinations of data that were not represented in the PTF development data set.

Patterns are more complicated in Fig. 5 compared with results in Fig. 4 derived from the direct K_s estimation. Inverse relationships between ϕ_e and OM can be found for a considerable range of soil properties with all three PTFs. Inverse relationships can be found at practically any sand, clay, and OM content. Extensive ranges of soil properties are observed for which at least one of the PTFs indicates such relationship (Fig. 5d).

DISCUSSION AND CONCLUSIONS

Given two soils with the same physical properties, but different OM contents, which one will have greater K_s? Raw data shows weak, but in two cases significant inverse relationship between OM and K_s. Both published and newly developed PTFs provide strong indication that negative relationship between OM and K_s may exist for a wide range of soils. One possible explanation for this can be derived from the fact that soil OM retains water well. In a complex effect on soil hydraulic conditions, OM not only enhances (potential) hydraulic conductivity by creating larger ϕ in the soil, but also reduces that by retaining water, allowing less water to flow freely. Organic matter may also affect the pore-size distribution of the soil through soil structure development, which also influences hydraulic conductivity. The modification of soil structure with the increase of OM content may replace larger cracks and clods with more aggregated material with more tortuous and thin pathways for water to go. The extent of these effects may be different for different soils. Our analysis did not allow to clearly define the range of soil properties that show inverse relationship between OM content and K_s.

The expected effect of increasing OM content on D_b has not been considered when we directly estimated K_s by the three new PTFs. It might affect the estimations if both variables are inputs to the predictive equation. Certainly, the research in this subject needs to be advanced. We note, however, that when ϕ_e was estimated, D_b was not used as input. Moreover, we estimated ϕ using texture and OM data. Bulk density can be calculated from ϕ, so, in practical terms, we estimated D_b. This means that the effect of OM on D_b was implicitly included in our ϕ_e models. Still, estimations showed the inverse relationship between OM and K_s for a wide range of soils (Figure 5).

It can be argued that different type/quality of OM has different effect on hydraulic properties. Such argument is of course true. Accumulation of lignitic material may not improve soil structure. Movable organic colloids may clog the soil, especially if there is some appreciable level of soil salinity. Unfortunately, information on the quality of OM present in the soil is usually not available in soil hydraulic databases. An effort to include such information can be rewarding.

Databases of soil hydraulic properties may also contain a number of swelling soils (i.e., Vertisols) that would have high OM contents but low K_s. Such soils could cause bias toward negative relation between OM content and K_s. Soils with such characteristics were rare in the three databases we used.

Our findings about the relationship of OM and K_s contradict the results of other authors, (Auerswald, 1995; Mbagwu and Auerswald, 1999; Lado et al., 2004). Data collection to those studies was specifically designed to examine the relationships between a number of soil hydraulic properties and soil aggregation. Those studies typically involved measurements of soil hydraulic properties in repacked soil columns. Databases that we used have not been specifically assembled for the purpose of this work. Some characteristics of the HUN, EUR, and USA data sets are just the opposite to those used by the above authors: they consist of a large number of soil samples; soil hydraulic properties have been measured on undisturbed soil cores; data are limited to the commonly determined soil physical properties. It is

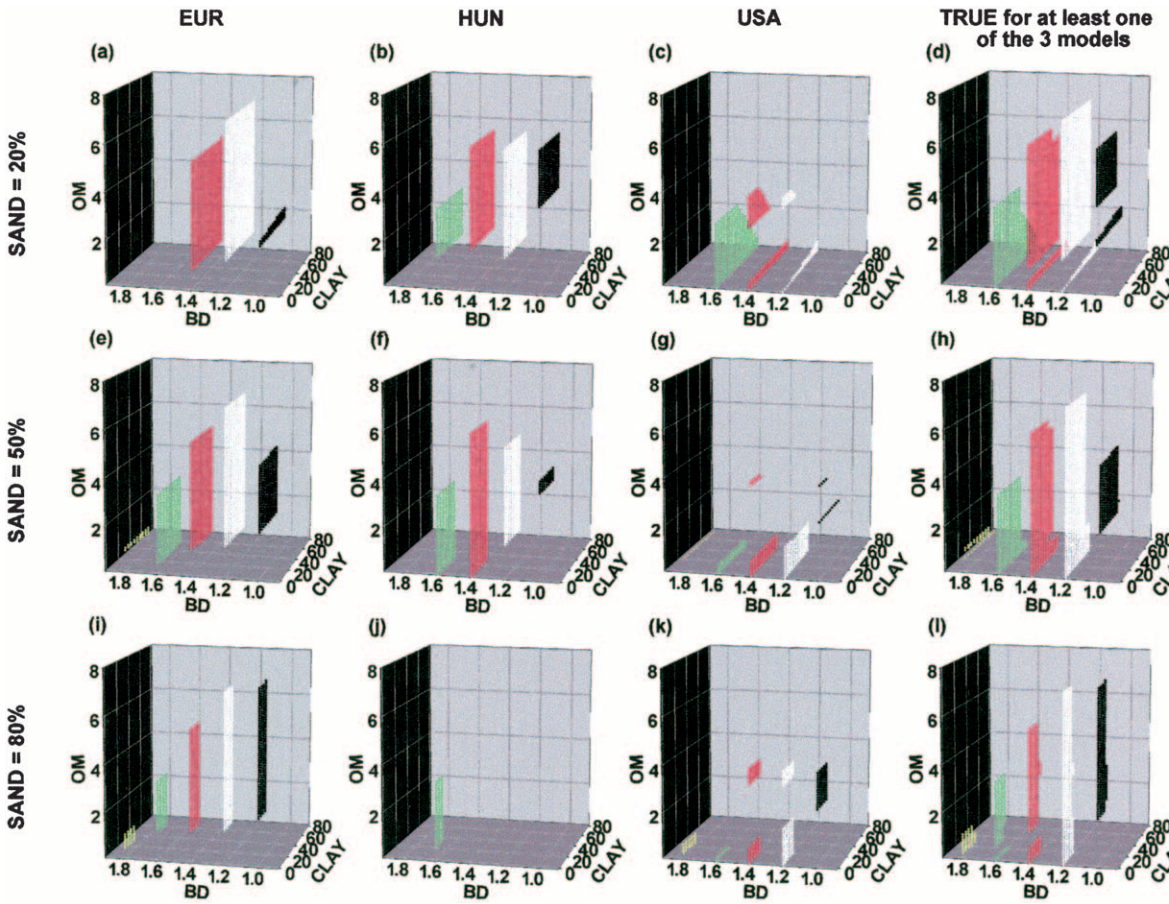

Fig. 4. Sensitivity of K_s to changes in organic matter (OM) content, at three levels of sand content (20, 50, 80%) and five levels of bulk density (D_b) (1.0, 1.2, 1.4, 1.6, 1.8 g cm^{-3}), estimated from three different data sets, using sand and clay content (%), D_b (g cm^{-3}), and OM content (%) as input. The range of soils is shown, for which the estimated K_s decreases when OM content is increased. Different colors designate soils with different levels of D_b. (EUR–the European data set; HUN–the Hungarian data set; USA–the U.S. data set).

difficult to make a direct comparison between those studies and ours. Nevertheless, analysis of the raw data, PTFs developed by others, and two approaches to estimate K_s from three different data sets give reasons to believe that OM and K_s are not in straight positive correlation for any soil. Users of soil hydraulic databases and PTFs will have to face this matter in their applications. Further research is recommended to quantify OM–D_b–K_s relationships in the soil.

APPENDIX

Algorithms to Estimate K_s, ϕ, and θ_{33}, Developed from the USA Data Set

Symbols: SA, sand (%); CL, clay (%); D_b, bulk density (g cm^{-3}); OM, organic matter content (%); K_s, saturated hydraulic conductivity (cm d^{-1}); ϕ, total porosity (cm^3 cm^{-3}); θ_{33}, water content at −33kPa matric potential (cm^3 cm^{-3}); x_1–x_4 and z_1–z_6, auxiliary variables.

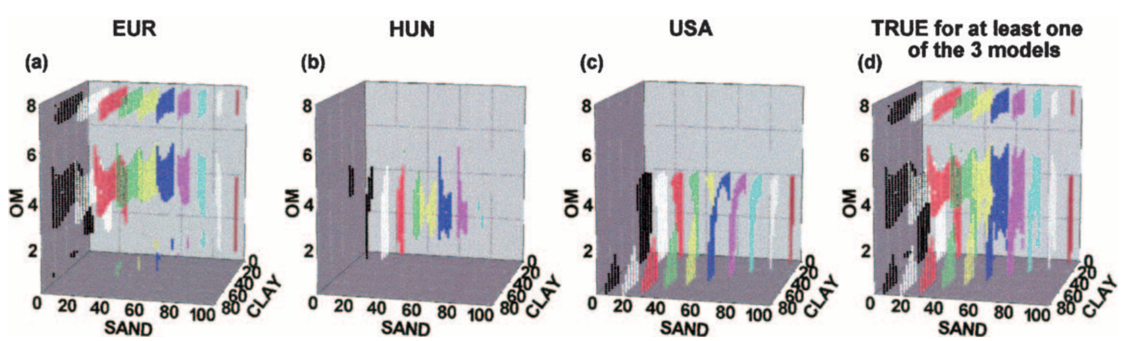

Fig. 5. Sensitivity of the effective porosity (ϕ_e) to changes in organic matter (OM) contents, at selected sand contents (5–95% by 10% increments), as estimated from three different data sets, using sand and clay content (%) and OM content (%) as input. The range of soils is shown for which the estimated ϕ_e decreases when the OM content is increased. Different colors designate soils with different levels of sand content. (EUR–the European data set; HUN–the Hungarian data set; USA–the U.S. data set).

$$x_1 = -3.663 + 0.046 \times \mathrm{SA}$$
$$x_2 = -0.887 + 0.083 \times \mathrm{CL}$$
$$x_3 = -9.699 + 6.451 \times \mathrm{D_b}$$
$$x_4 = -0.807 + 1.263 \times \mathrm{OM}$$
$$z_1 = -0.428 + 0.998x_1 + 0.651(x_1)^2 + 0.130(x_1)^3$$
$$z_2 = 0.506x_1 - 0.188x_2 - 0.327x_3 - 0.094x_4$$
$$\begin{aligned} z_3 = {} & -0.268 + 0.885z_1 + 0.544z_1^2 - 0.682z_1^3 + \\ & 0.320z_2 - 0.134z_1z_2 + 1.119z_1^2z_2 + 0.050z_2^2 - \\ & 0.645z_1z_2^2 + 0.160z_2^3 + 0.126x_4 - 0.144z_1x_4 - \\ & 0.372z_1^2x_4 + 0.247z_2x_4 + 0.795z_1z_2x_4 - 0.344z_2^2x_4 + \\ & 0.038x_4^2 - 0.071z_1x_4^2 + 0.020z_2x_4^2 - 0.015x_4^3 \end{aligned}$$
$$\begin{aligned} z_4 = {} & 0.102 + 1.383z_3 + 0.302z_3^2 + 0.103z_3^3 + \\ & 0.331x_2 + 0.693z_3x_2 + 0.541z_3^2x_2 + 0.198x_2^2 + \\ & 0.429z_3x_2^2 + 0.092x_2^3 + 0.060x_3 + 0.277z_3x_3 + \\ & 0.417z_3^2x_3 + 0.242x_2x_3 + 0.929z_3x_2x_3 + \\ & 0.319x_2^2x_3 + 0.026x_3^2 + 0.094z_3x_3^2 + 0.116x_2x_3^2 \end{aligned}$$
$$K_s = 10^{0.571 + 0.956z4}$$
$$\begin{aligned} z_5 = {} & -0.060 - 0.509x_1 - 0.518x_1^2 - 0.133x_1^3 - \\ & 0.737x_2 - 0.899x_1x_2 - 0.217x_1^2x_2 - 0.027x_2^2 + \\ & 0.015x_2^3 + 0.823x_4 - 0.173x_1x_4 - 0.111x_1^2x_4 - \\ & 0.050x_2x_4 - 0.041x_1x_2x_4 - 0.013x_2^2x_4 - \\ & 0.140x_4^2 - 0.047x_1x_4^2 - 0.021x_2x_4^2 + 0.006x_4^3 \end{aligned}$$
$$\phi = 0.433 + 0.058z_5$$
$$\begin{aligned} z_6 = {} & 0.109 + 0.574x_1^2 + 0.169x_1^3 + 0.913x_2 + \\ & 1.204x_1x_2 + 0.439x_1^2x_2 + 0.371x_2^2 + 0.238x_1x_2^2 + \\ & 0.037x_2^3 + 0.282x_4 + 0.288x_1x_4 + 0.109x_1^2x_4 + \\ & 0.271x_2x_4 + 0.251x_1x_2x_4 + 0.120x_2^2x_4 - \\ & 0.060x_4^2 - 0.022x_1x_4^2 - 0.025x_2x_4^2 + 0.009x_4^3 \end{aligned}$$
$$\theta_{33} = 0.165 + 0.112z_6$$

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